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RoboLeader: An Intelligent Agent for Enhancing Supervisory Control of Multiple Robots

by Jessie Y. C. Chen, Michael J. Barnes, Zhihua Qu, and Mark G. Snyder

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14. ABSTRACT

We developed an intelligent agent, RoboLeader, that could assist human operators in controlling a team of robots. More specifically, RoboLeader was able to help the operators with their route planning tasks. Although there were no significant differences between the RoboLeader and Baseline conditions for target detection performance, participants in the RoboLeader group reduced their mission completion times by ~13% compared to Baseline. We also compared the operators' target detection performance in the four-robot and eight-robot conditions. The results showed that the participants detected significantly fewer targets when there were eight robots present, compared to the four-robot condition; participants with higher spatial ability, however, detected more targets than did those with lower spatial ability. Participants also experienced significantly higher workload with eight robots, and those with better attentional control reported lower workload than did those with poorer attentional control. Females also reported significantly higher workload than did males.

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1. Introduction

1.1 Background

Unmanned vehicles (UVs) are being used more frequently in military operations, and the types of tasks they are being used for are evolving in complexity. In the future battlefield, Soldiers may be given multiple tasks to perform concurrently, such as navigating a UV while conducting surveillance, maintaining local security and situational awareness, and communicating with fellow team members. To maximize human resources, it would be ideal to designate a single operator to supervise multiple UVs simultaneously. However, research has shown that human operators are often unable to control multiple robots/agents simultaneously in an effective and efficient manner (Chen, Durlach, Sloan, and Bowens, 2008; Schurr, 2007). Additionally, as the size of the robot team increases, the human operators may fail to maintain adequate situational awareness when their attention has to constantly switch among the robots, and their cognitive resources may be overwhelmed by the intervention requests from the robots (Wang, Wang, and Lewis, 2008; Wang, Lewis, Velagapudi, Scerri, and Sycara, 2009). Wang et al. (2009) reviewed a number of studies on supervisory control of multiple ground robots for target detection tasks and concluded that “the Fan-out plateau lies somewhere between 4 and 9+ robots depending on the level of robot autonomy and environmental demands” (p. 143).

Research has shown that autonomous cooperation between robots can aid the performance of the human operators (Wang et al., 2008) and enhance the overall human-robot team performance (Schurr, 2007). Wang et al., (2009) suggested that automating navigation-related tasks (e.g., path-planning) is more important than “efforts to improve automation for target recognition and cueing” (p.146) in the context of controlling a large team of robots. However, in the foreseeable future, human operators’ involvement in mixed-initiative (i.e., human-robot) teams will always be required, especially for critical decision making. Human operators’ decision making may be influenced by “implicit goals” about which the robots are not aware (i.e., the goals are not programmed into the behaviors of the robots; Linegang et al., 2006). In addition, the real-time development on the battlefield may require the human operator to change the plan for the robot team and/or for the individual robots. Therefore, effective communication between the human operator and the robots is critical in ensuring mission successes.

Research has been conducted on ways to enhance human-robot communication (Stubbs, Wettergreen, and Nourbakhsh, 2008). For example, researchers at Carnegie Mellon University demonstrated the effectiveness of a robot proxy to enhance shared understanding between the human operator and the robot in an exploration task (Stubbs et al., 2008). The communication mechanism was based on a common ground collaboration model and was able to improve the human operator performance in the following areas: more accurate plans, more efficient planning

(fewer planning repetitions), faster and more efficient task performance, and better mental modeling of the capabilities of the robot (Stubbs et al., 2008).

1.2 Current Study

In the current study, we investigated whether RoboLeader, a robotic surrogate for the human operator, and an intelligent agent that could interpret the operator's intent and issue detailed command signals to a team of robots of lower capabilities, could enhance the overall human-robot teaming performance. With the RoboLeader capabilities, dependence on operator instructions was reduced and the level of autonomy in operation of UVs was improved by implementing algorithms including real-time path planning, cooperative control, and multi-objective decision of tactical strategies. These algorithms were stacked, and the operator only needed to make high-level decisions (Chuyuan, Qu, Pollak, and Falash, 2008; Howard, Qu, and Conrad, 2008; Qu, Wang, and Hull, 2008; Qu, Wang, and Plaisted, 2004; Yang, Qu, Wang, Conrad, and Hull, 2007). These algorithms resided in RoboLeader and enabled the operator to control a team of robots through a single user interface. RoboLeader was able to assess the feasibility of the operator's plans by simulating their execution.

The effects of individual differences factors on operator performance were also evaluated. More specifically, the effects of individual differences in spatial ability (SpA) and perceived attentional control (PAC) on the operators' robotics control were investigated, as well as multitasking performance. Lathan and Tracey (2002) demonstrated that people with higher SpA performed better in a teleoperation task through a maze; they finished their tasks faster and had fewer errors. Lathan and Tracey suggested that military missions can benefit from selecting personnel with higher SpA to operate robotic devices. Our previous studies also found SpA to be a good predictor of the operator's robotics performance (Chen et al., 2008). Additionally, we examined the relationship between attentional control and multitasking performance. Several studies have shown that there are individual differences in multitasking performance, and some people are less prone to performance degradation during multitasking conditions (Rubinstein, Meyer, and Evans, 2001). There is evidence that people with better attentional control can allocate their attention more flexibly and effectively (Derryberry and Reed, 2002). This was partially confirmed by Chen and Joyner (2009) with the caveat that other studies showed that those with low PAC actually performed better with high false alarm target indictors compared to higher PAC participants, and worse when the target indictors evinced a high miss rate (Chen and Terrence, 2009).

2. Method

2.1 Participants

Thirty individuals (17 males and 13 females, mean age of 24–73 years) from the Orlando, FL area participated in the study. They were compensated $15/hr for their time.

2.2 Apparatus

2.2.1 Simulator

The Mixed Initiative Experimental (MIX) Testbed was modified and used as the simulator (Barber, Davis, Nicholson, Finkelstein, and Chen, 2008). The MIX Testbed is a distributed simulation environment for investigation into how unmanned systems are used and how automation affects performance. The Operator Control Unit (OCU) of the MIX Testbed was modeled after the Tactical Control Unit developed under the U.S. Army Research Laboratory (ARL) Robotics Collaborative Technology Alliance (figure 1). This platform includes a camera payload and supports multiple levels of automation. Users can send mission plans or teleoperate the platform with a joystick while being provided a video feed from the camera payload. Typical tasks include reconnaissance and surveillance.

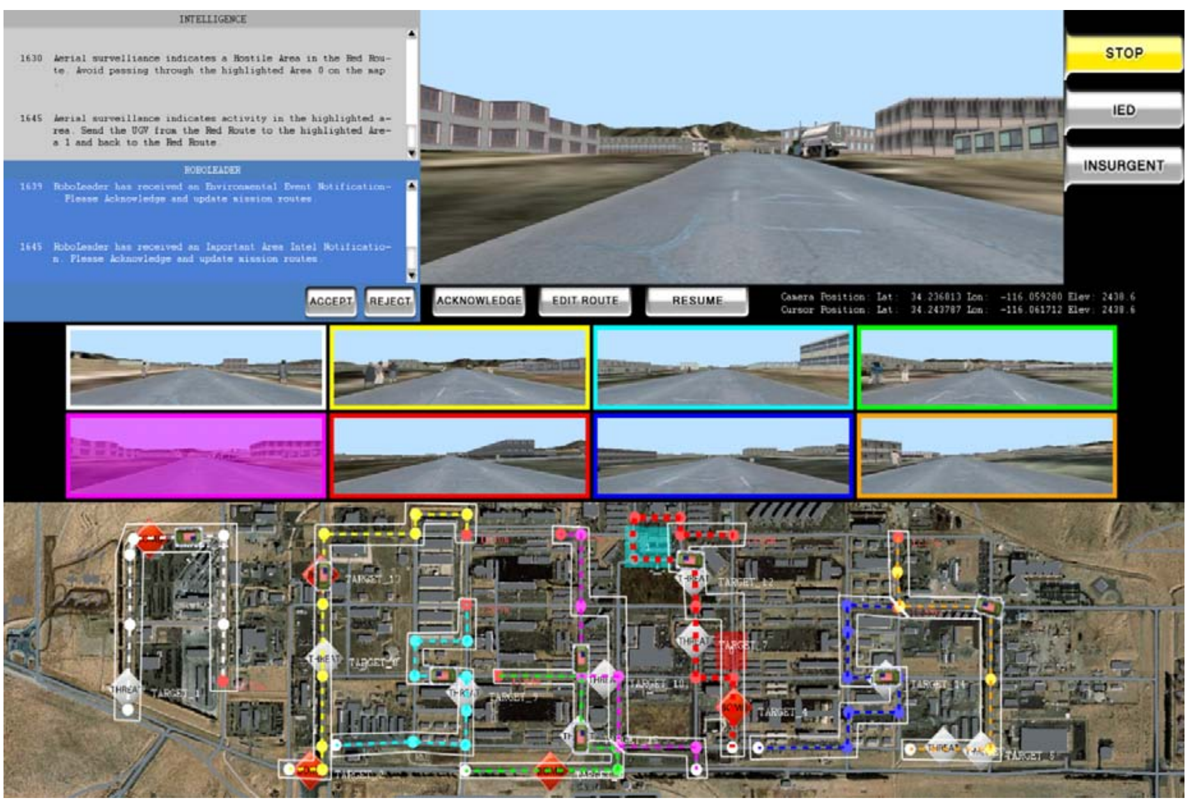

Figure 1. RoboLeader user interface.

2.2.2 RoboLeader Algorithm

2.2.2.1 General overview. The RoboLeader utility consists of several components—interface, control loops, and path generator. The interface pulls all necessary vehicle/environmental data from the simulation environment and supplies the control loops and path generator with all required information. The control loops support a modular design, in that additional capabilities can be added to the system with little or no modification to existing systems. The path generator, based on the A-Star algorithm, was implemented with concepts from vector mechanics. Because vector mechanics was used, sets of search criterion were developed that give the path generator unique behavior as compared to typical matrix search algorithms. The path generator can be given a start point and an end point to navigate towards, and the algorithm will "home in" on the intended destination. The path generator has the ability to wrap around the destination until an entry path is found.

While the path generator is responsible for calculating new routes for the vehicle, the finished path solution is typically formed in segments and stitched together by the control loops in order to reach the final path solution. Depending on the situation, different path formation behaviors must be exhibited by the utility. The control loops are primarily responsible for assigning different behaviors to the finished path solution. Three typical vehicle/environmental conditions may be encountered during reconnaissance missions, and each requires different path planning schemes; they are blocked/hostile areas, high priority areas, and vehicle disablement. The different behaviors exhibited for each of the conditions, and operations required by the utility, are summarized as follows:

- Hostile/blocked area: The RoboLeader utility must determine the vehicles affected by this condition by analyzing the pre-determined path routes to see if any vehicle routes pass through this area. This task is executed by the control loops. If a vehicle path is found to pass within a hostile/blocked area, the control loops determine start and end points that correspond to navigable locations outside of the hostile/blocked area. These points are then passed to the path generator, and a new route is calculated tightly around the area from start point to end point. It is important to tightly navigate around the hostile area and rejoin with the existing path to salvage as much of the original reconnaissance route as possible. This newly formed path segment is passed back to the control loops for further processing. The control loops create the finished path solution by merging the segment into the original vehicle route. The finished solution is then passed back to the OCU for operator approval or modification.

- High priority area: During a reconnaissance mission, resources may need to be urgently diverted to a new high priority location. Under this scenario, the control loops search through all of the vehicles involved in the mission and determine which ones must be reallocated to the high priority location. The control loop charged with handling this scenario computes a start point and end point corresponding to the vehicles' current

positions and an entry point into the high priority location, respectively. The path generator computes a path between these points and passes the result back to the control loops, which then merge the new solution into the portion of the original path already traversed. The control loop then determines an exit point from the high priority location and also identifies the location of the originally intended destination. The path generator is called up again, and a second path solution is formed, which leads from the high priority area to the original destination. The control loop then forms the final solution.

- Disabled vehicle: In the event a vehicle is disabled, a new route must be formed from the vehicle's current location to the original destination for use by recovery forces. The control loop for this condition first identifies the vehicle's current location and assigns this position as the start point for the path generator. The destination of the vehicle's original pre-planned route is then set as the end point. The path generator is then called up to form the path. The control loop then merges this new path segment into the portion of the vehicle's path, which has already been traversed.

Figure 2 shows a general flow of information through the utility. *A* indicates vehicle and or environmental data supplied to the path generator, and *B* represents the calculated path produced by the generator being returned to the testbed. The main control loops are responsible for calling the path generator and all other support functions, depending on the previously addressed situations. In addition to this, the control loops are also responsible for collecting and configuring data from the interface, and formatting the data for use in the path generator. The next three sections—interface, control loops, and path generator—provide greater detail into the functional operation of these components.

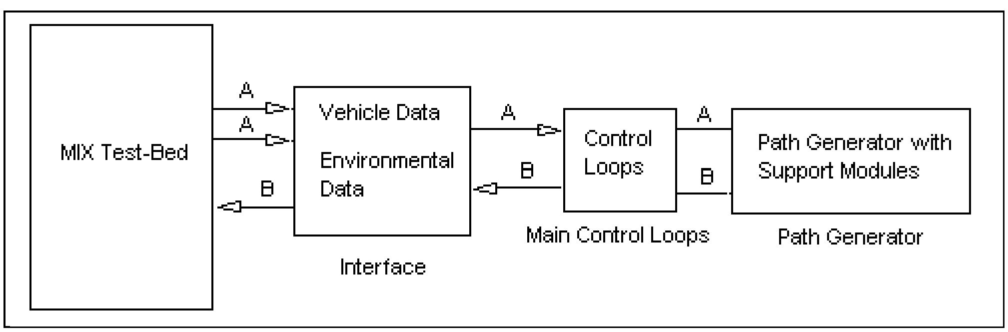

Figure 2. Data flow between testbed and path generator.

2.2.2.2 Interface. The algorithms implemented in RoboLeader's current design require full knowledge of the detected environmental events and various instantaneous vehicle states. This data is passed from the MIX Testbed to the RoboLeader algorithms through an interface connecting the two. The interface thus forms the structure from which the RoboLeader utility polls data. The interface is comprised of a set of C++ vectors that contain data classes that store the required information. Each of the classes, when populated with data, is loaded into its respective vector. In other words, the vehicle vector contains the vehicle classes, the waypoint

vector contains the waypoint classes, and the area vector contains the area classes. Each class stores information with regard to one specific entity. For instance, a vehicle class contains state data for only one vehicle. The vehicle vector then contains all of the classes describing all vehicles in the simulation. The three primary data classes of vehicle, waypoint, and area, and the data they contain, are described next.

- Vehicle Class. The vehicle class contains all vehicle state data, such as vehicle identification number, pre-planned route (contained in waypoint class and nested within this class), disablement (indicates if the vehicle has been disabled or not), and the environmental tag, which relates a vehicle to certain events in the environment.

- Waypoint Class. The waypoint class contains waypoint data and waypoint visited status for a specific vehicle's pre-planned route.

- Area Class. The area class contains geographic position information pertaining to regions of interest, such as blocked/hostile areas, zones of operation, or high priority areas requiring reconnaissance.

2.2.2.3 Control loops. The main control loops query the interface looking for vehicles tagged with hostile, high priority, or disabled designations, and call up the path generator in the proper sequences in order to construct path solutions appropriate for the given situation. Figure 3 illustrates the flow of control between the path generator, the main control loops, and the interface. Within the interface block, the vehicle and area vectors are shown, which contain data that triggers a specific loop (center block of figure 3) used to formulate different path solutions. Three control loops are used, and each loop accesses the vehicles environmental tag. Depending on the tag, one of the three loops may be called up to generate a solution specific to one of the three conditions. If a vehicle is not tagged, all three loops ignore that vehicle. Once a tag is identified by a specific loop, that loop will compute the proper path generator parameters and initiate the generator. Once the path generator forms a solution, each control loop will merge the new solution into the original path creating the final desired path. This piecing together of new paths with old paths is dependant on the desired behavior.

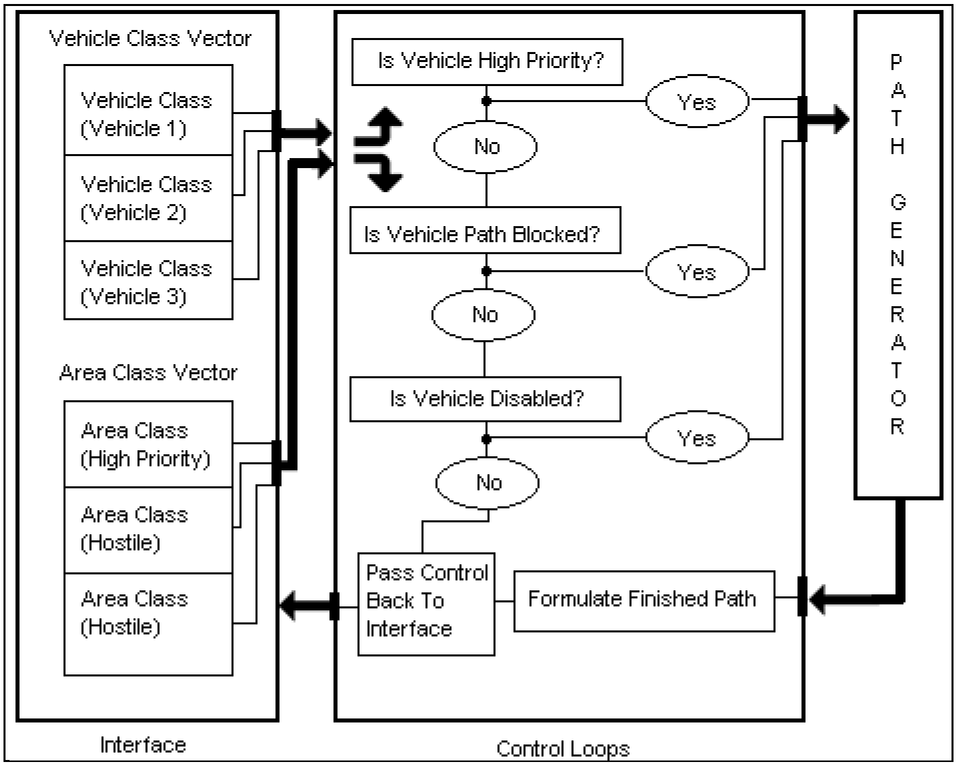

Figure 3. Interaction of RoboLeader sub-components.

2.2.2.4 Path generator. The base operation of the path generator is described in this section. As mentioned before, the generator must be given a starting and ending point in order to calculate a path. Once start and end points are assigned, the generator calculates a vector between these two points that remains constant throughout the path calculation (figure 4). This vector is called the main resultant and forms a guide for all of the path generator's decision making operations. Once the main resultant is established, a second set of vectors is calculated, which spans each intersection that connects to the start point and the end point—i.e., a vector is calculated to the end point from each intersection that connects with the start point. The shortest vector magnitude distance is then chosen, the path generator moves to that intersection, and the process occurs repeatedly until the destination is reached. Figure 5 shows a depiction of this process.

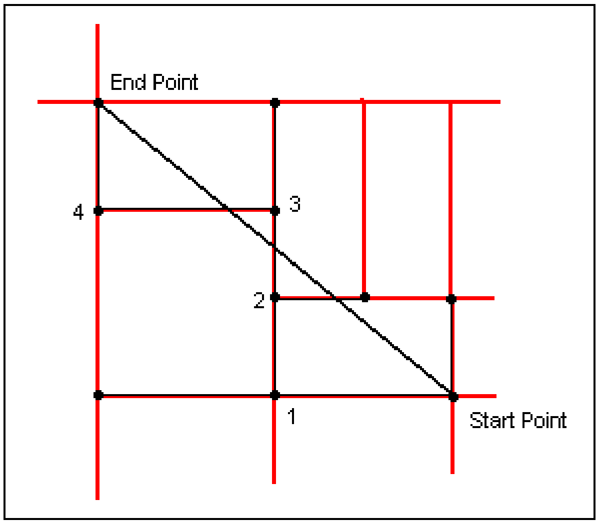

Figure 4. Vector/street grid.

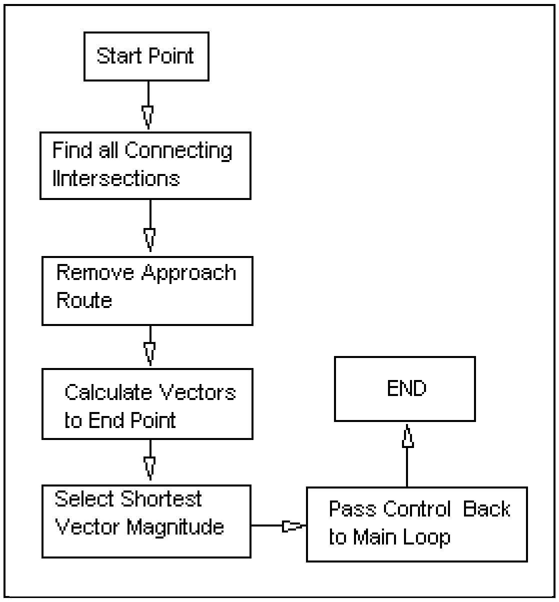

Figure 5. Path generator operations.

Each step the path generator takes through the street grid is analyzed based on its connection with adjacent intersections, and a decision is made based on the shortest distance to the end point (figure 4). Because vectors maintain constant connection with the end point, the generator can "home in" on its destination until an entry path to the end point is found. The next section describes the add-on behavior for which the main control loops augment the path generator.

The job of the path generator is straight-forward in nature. The objective is to efficiently determine a path from one point to another through a street grid. As mentioned before, however, the control loops provide additional behavior to the path generator and are also responsible for calling the correct processing function. The illustration in figure 6 shows a simplified version of

the processes the control loops must execute. On the right-hand side of figure 6, each of the three trigger conditions that call up the appropriate processing routine can be seen. Using the high priority condition as an example, figure 7 depicts a simplified flow of control that occurs within the “Call High Priority Processing Routine”. In this case, the path generator is called twice—once to get to the high priority area, and then a second time to navigate back to the intended destination.

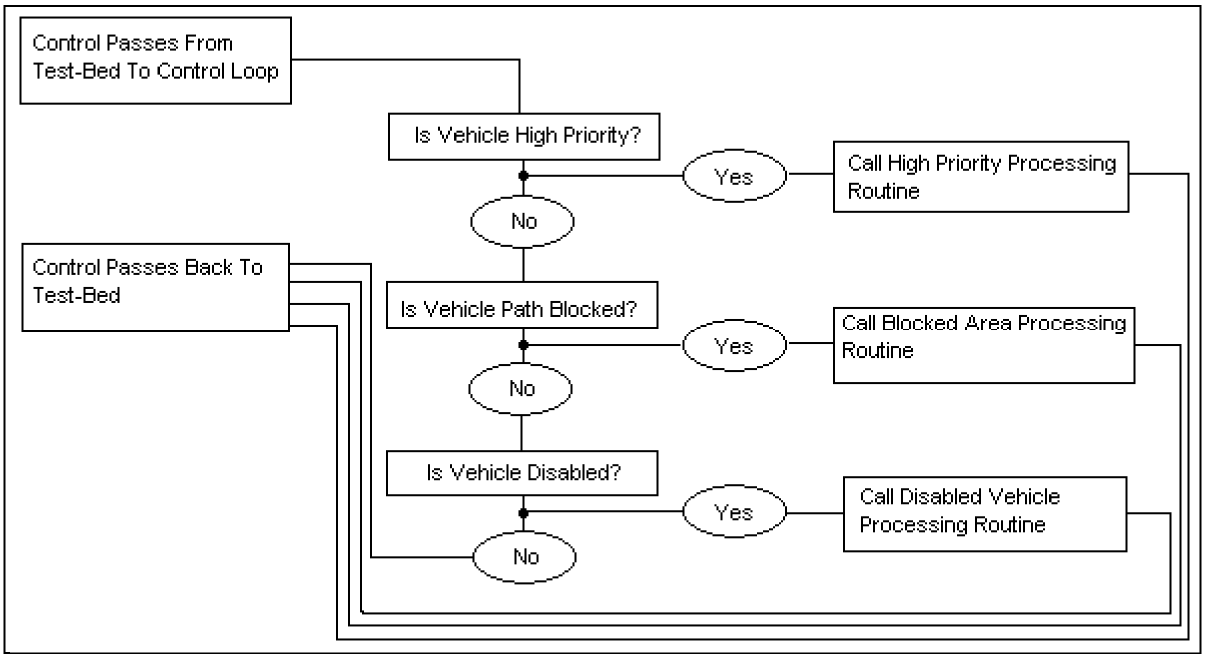

Figure 6. Main control loop.

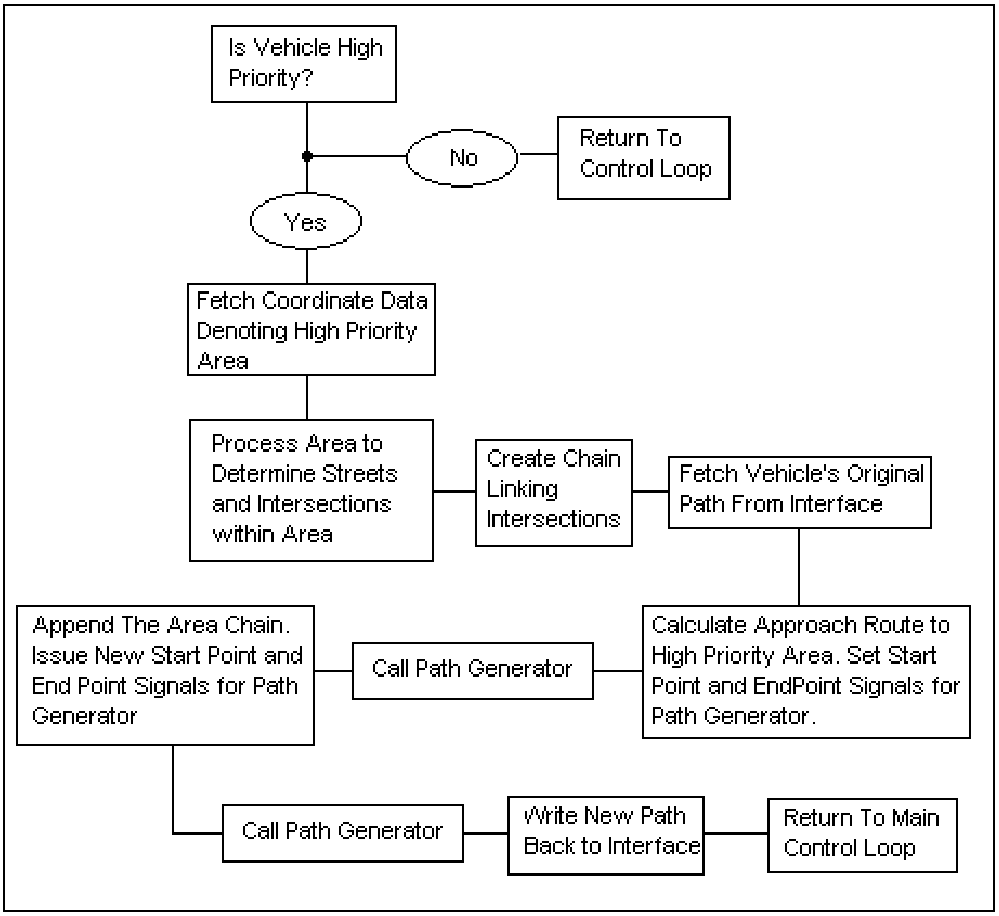

Figure 7. High priority condition processing loop.

The modular nature of the RoboLeader utility should be evident at this point. New features and capabilities can be added to the utility by simply adding a new control loop whose operation is triggered by specific data reaching the interface. Specific algorithms comprising the new capability are then nested within that control loop.

2.2.3 Surveys and Tests

A demographics questionnaire (appendix A) was administered at the beginning of the training session. Since the RoboLeader user interface employed several colors to display the plans for the robots, and normal color vision was required in order to effectively interact with the system, an Ishihara color vision test (with nine test plates) was administered via PowerPoint[1] presentation. The RoboLeader user interface employed several colors to display the plans for the robots and normal color vision was required in order to effectively interact with the system. A questionnaire on Attentional Control (Derryberry and Reed, 2002; appendix B) was used to evaluate participants' perceived attentional control. The Attentional Control survey consists of 21 items, and measures attention focus and shifting. The scale has been shown to have good

[1] PowerPoint is a registered trademark of Microsoft Corporation, Redmond, WA.

internal reliability (α = .88). The Cube Comparison Test (Ekstrom, French, and Harman, 1976) and the Spatial Orientation Test (Gugerty and Brooks, 2004) were used to assess participants' spatial ability. The Cube Comparison Test required participants to compare, in 3 min, 21 pairs of six-sided cubes and determine if the rotated cubes were the same or different. The Spatial Orientation Test, modeled after the cardinal direction test developed by Gugerty and his colleagues (2004), is a computerized test consisting of a brief training segment and 32 test questions. Both accuracy and response time were automatically captured by the program. Participants' perceived workload was evaluated using the computerized version of the National Aeronautics and Space Administration (NASA)-Task Load Index (TLX) questionnaire (appendix C), which used a pairwise comparison weighting procedure (Hart and Staveland, 1988). The NASA-TLX is a self-reported questionnaire of perceived demands in six areas: mental, physical, temporal, effort (mental and physical), frustration, and performance. Participants evaluated their perceived workload level in these areas on 10-point scales, as well as completing pairwise comparisons for each subscale.

2.3 Procedure

Participants were randomly assigned to the RoboLeader group or the Baseline (no RoboLeader) group before their session started. After being briefed on the purpose of the study and signing an informed consent form, participants completed the demographic questionnaire and were administered a brief Ishihara color vision test to ensure they had normal color vision. After the color vision test, participants completed the Attentional Control survey and the two spatial ability tests. Participants then received training and practice on the tasks they would need to conduct. Training was self-paced and was delivered by PowerPoint slides, which showed the elements of the OCU, steps for completing various tasks, several mini-exercises for practicing the steps, and exercises for performing the robotic control tasks. Each participant had to demonstrate that he or she could recall all the steps for performing the tasks without any help by the end of the training session; the training session lasted ~1 h.

The experimental session also lasted about 1 h and immediately followed the training session. The experimental session had two scenarios, each lasting ~30 min, in which participants used their robotic assets to locate 20 targets (i.e., 10 insurgents carrying weapons and 10 improvised explosive devices [IEDs]) in the remote environment. There were four robots available in one scenario and eight robots in the other scenario. The order of scenarios was counter-balanced across participants.

When each scenario started, the robots began following pre-planned routes, at which time the operator's task of monitoring the environment and detecting targets (insurgents and IEDs) began. The robots did not have Aided Target Recognition capability; therefore, the participants had to detect the 10 insurgents and 10 IEDs by themselves. For the insurgent targets, participants were instructed to use their computer mouse to click on the targets (i.e., to "lase" them) as soon as they were detected. The "lased" insurgents were then automatically displayed on the map. For

the IED targets, however, participants clicked on an IED button on the interface, and then marked the location of the IEDs on the map. Additionally, there were friendly dismounted Soldiers and civilians in the simulated environment to increase the visual noise for the target detection tasks. The participants were told that their objective was to finish reconnoitering the area using their robotic assets in the least amount of time possible. Consequently, when re-planning a route, the participant and/or RoboLeader had to consider both the effectiveness and efficiency of the new route. For example, situations in which a robot completed its route quickly but did not cover much ground or covered a lot of ground but was slow to finish would be suboptimal in comparison to re-planning that efficiently (i.e., less time) covered a lot of ground.

In each scenario, there were six events that required revisions to a robot's current plan/route. Once an event transpired, the Baseline participants needed to notice that the event had occurred, and then re-route the robot that was affected by the event. For those in the RoboLeader condition, the RoboLeader would recommend plan revisions to the operator, who could either accept the plans or modify them as necessary. Out of these six events, three were "bottom-up" (i.e., unanticipated obstacles detected by the robots that obstructed their navigation) and three were "top-down" (i.e., intel that the human operator received from the intel network). Given that the events led to obstruction (e.g., vehicles in the path, hostile area), the RoboLeader and the participant needed to avoid re-routing through these areas, in addition to avoiding areas where insurgents or IEDs were already detected. Additionally, in the RoboLeader condition, RoboLeader would recommend new routes for robots that finished first if it decided that the overall mission time could be reduced by redirecting those robots to the unsearched areas.

Each scenario also contained five situation awareness (SA) queries, which were triggered based on time progression (i.e., three minutes into the scenario). The SA queries included questions such as, "which areas have the robots searched?" (participants were instructed to mark the searched areas on a blank map), "which of your robots is the closest to [Area of Interest]?", etc. The OCU screen was blank when an SA query was triggered, and only the SA query and the answer box were displayed on the screen. A list of SA queries is provided in appendix D.

There were two-minute breaks between experimental sessions. Participants' perceived workload (NASA-TLX) was also assessed after each experimental scenario.

2.4 Experimental Design and Performance Measures

The study was a 2 × 2 mixed design; RoboLeader (with or without RoboLeader [Baseline]) was the between-subject variable and the number of Robots used in the scenario (four vs. eight) was the within-subject variable. Performance measures included the number of targets located and identified, the operator's situational awareness of the mission environment, and awareness of the status of the individual robots. A mixed-design analysis of covariance (ANCOVA) with RoboLeader (with or without RoboLeader) as the between-subject factor and number of Robots (four vs. eight) as the within-subject factor was used to evaluate the operator performance differences among the four conditions. Participants' spatial ability (SpA), which was a

composite score of the two spatial tests, and their attentional control survey score were used as covariates.

3. Results

3.1 Target Detection Performance-Insurgents

Table 1 lists several measures related to target detection performance (insurgents and IEDs) and SA queries, as well as subjective workload. The analysis revealed that the robot's condition significantly affected the number of insurgent targets detected—$F(1,26) = 21.716$, $p < 0.0001$. Participants detected significantly fewer insurgents when there were eight robots compared with the condition when four robots were available. Participants with higher SpA detected significantly more insurgents than did those with lower SpA—$F(1,26) = 6.633$, $p < 0.05$ (figure 8). The effects of RoboLeader and attentional control were not statistically significant.

Table 1. Operator task performance and workload assessments (standard deviations are presented in parentheses).

	Baseline		**RoboLeader**	
Measures	4 Robots	8 Robots	4 Robots	8 Robots
Target Detection (Insurgents)	6.667[a] (1.345)	5.000[b] (1.690)	7.000[a] (2.035)	5.533[b] (2.200)
Target Detection (IEDs)	8.333[a] (1.291)	7.267[b] (1.668)	8.400[a] (1.502)	7.000[b] (2.070)
SA Queries	2.317[a] (0.858)	1.333[b] (1.289)	2.433[a] (1.128)	1.192[b] (1.012)
Perceived Workload	67.38[a] (16.33)	71.40[a] (18.10)	61.27[a] (14.85)	67.11[a] (14.69)

Note: Statistics with the same superscript are not significantly different from one another

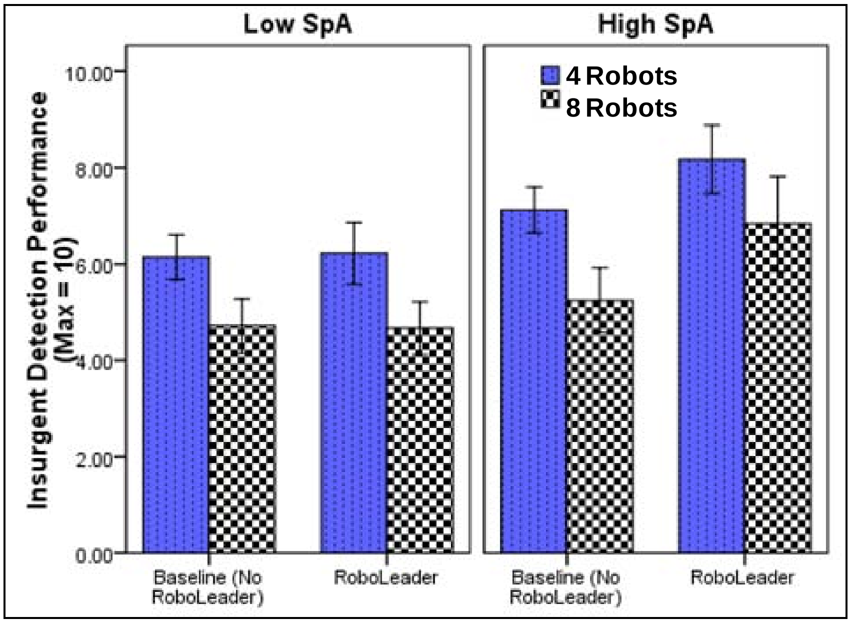

Figure 8. Insurgent detection performance.

3.2 Target Detection Performance-IEDs

The analysis showed that participants detected significantly fewer IEDs when they had eight robots compared with the condition when four robots were available—$F(1,26) = 10.129$, $p < 0.005$. Participants with higher SpA detected significantly more IEDs than did those with lower SpA—$F(1,26) = 10.656$, $p < 0.005$ (figure 9). The effects of RoboLeader and attentional control were not statistically significant. There was a non-significant RoboLeader × SpA effect—$F(1,26) = 2.545$, $p = 0.12$. However, as is shown in figure 9, participants with higher SpA performed slightly better with RoboLeader compared with the Baseline condition; the same pattern was not observed for the lower SpA group.

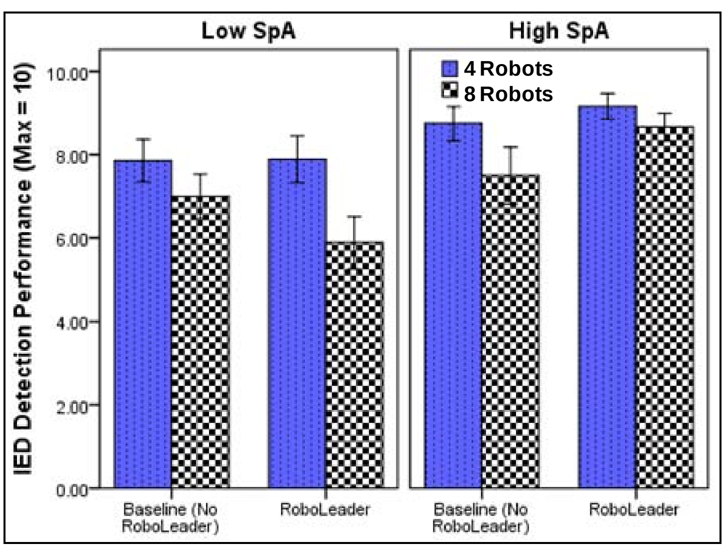

Figure 9. IED detection performance.

3.3 Situation Awareness Queries

The analysis revealed that participants' SA (figure 10) was significantly lower when they had eight robots compared with the condition when four robots were available—$F(1,26) = 13.309$, $p < 0.005$. None of the other factors were significant.

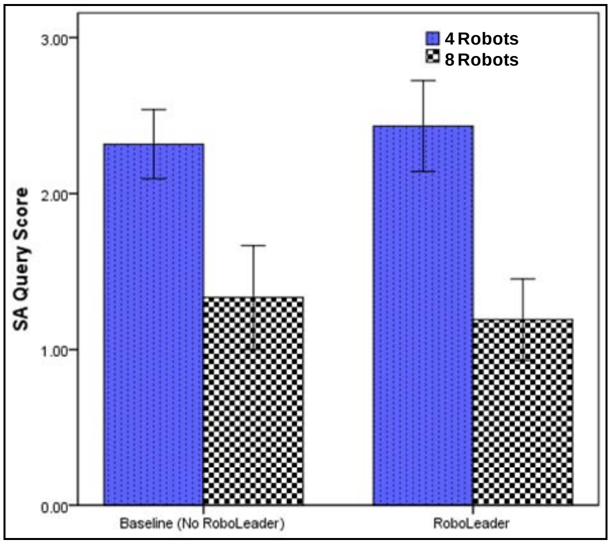

Figure 10. SA queries.

3.4 Perceived Workload

The analysis showed that participants experienced significantly higher workload when there were eight robots ($M = 69.26$) versus four robots ($M = 64.32$)—$F(1,26) = 4.947$, $p < 0.05$ (figure 11). Participants in the RoboLeader group assessed their workload slightly lower ($M = 64.11$) than did those in the Baseline group ($M = 69.38$). However, the difference failed to reach statistical significance. Participants with higher attentional control rated their workload as significantly lower than did those with lower attentional control—$F(1,26) = 7.229$, $p < 0.05$. The latter group also experienced significantly higher workload on five out of the six subscales when controlling eight robots, with the most differences in Frustration, Effort level, and Temporal demand. Notably, females reported significantly higher workload (4-robot: $M = 74.97$; 8-robot: $M = 77.05$) than did males (4-robot: $M = 56.18$; 8-robot: $M = 63.29$)—$F(1,28) = 12.162$, $p < 0.005$ (figure 11). The subscale data revealed that females were significantly more frustrated than their male counterparts, regardless of the number of robots. When there were four robots, females thought their performance was significantly worse than males; when there were eight robots, females' mental workload was significantly higher.

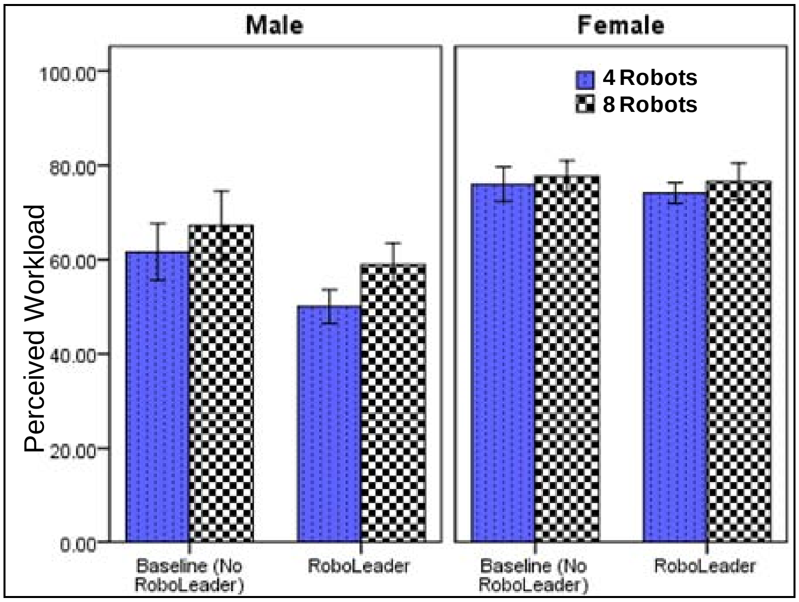

Figure 11. Perceived workload.

3.5 Operators' Interaction With the OCU

Participants' interaction with the OCU (e.g., clicks on the graphical user interface [GUI]) was further analyzed. During the experiment, participants needed to click on the smaller thumbnails (i.e., streaming videos from the robots) to enlarge the video image in order to identify targets. Participants in the Baseline group made significantly more clicks on the thumbnails than did those in the RoboLeader group—$F(1,25) = 8.329$, $p < 0.01$. They also made more clicks when they had eight robots compared with the four-robot condition—$F(1,25) = 132.229$, $p < 0.001$. Additionally, there was a significant RoboLeader × Robots interaction, as well as a significant Robots × SpA interaction—$F(1,25) = 5.637$, $p < 0.05$ and $F(1,25) = 4.291$, $p < 0.05$, respectively (figure 12). The difference between the four-robot and eight-robot conditions in the Baseline group was greater than that in the RoboLeader group. Additionally, participants with higher SpA tended to make more thumbnail clicks in the Baseline condition, but not in the RoboLeader condition. In addition to differences in the number of thumbnail clicks, participants in the RoboLeader group spent significantly less time completing their mission scenarios than did those in the Baseline group—$F(1,27) = 7.118$, $p < 0.05$. Participants in the RoboLeader group spent, on average, 20.68 min/scenario; on the other hand, those in the Baseline group spent 23.77 min/scenario.

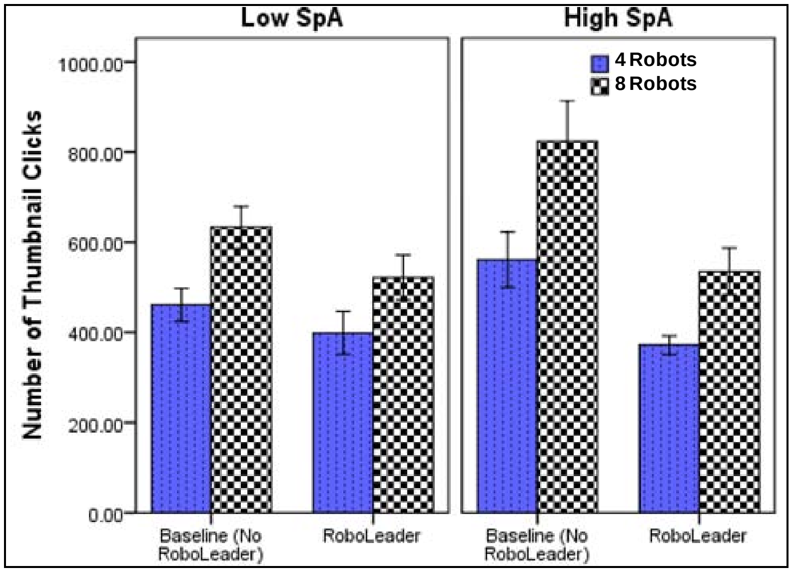

Figure 12. Thumbnail clicks.

4. Discussion

We developed an intelligent agent, RoboLeader, that could assist human operators in controlling a team of robots. More specifically, RoboLeader could help the operators with their route planning tasks. Although we did not find significant differences in target detection performance between the two groups, participants in the RoboLeader group completed their missions in significantly less time than did those in the Baseline group. On average, RoboLeader saved the participants ~3 min for missions lasting 20 or more min. This finding was expected, given the assistance the participants received from RoboLeader in the path-planning tasks. On the other hand, participants in the RoboLeader group exhibited significant complacency behavior compared with their Baseline group counterparts. More specifically, the RoboLeader participants, especially those with higher SpA, made significantly fewer clicks on the thumbnails of the streaming videos from the robots (to look for targets), compared with the Baseline group participants. While the number of clicks did not directly translate into a greater number of targets detected (i.e., the correlation was not significant), this striking difference in the way the operators interacted with the OCU based on the presence of RoboLeader needs to be further investigated.

We compared the operators' target detection performance in the 4-robot and 8-robot conditions. The results showed that the participants detected significantly less insurgents when there were eight robots compared to the four-robot condition, indicating less efficiency with more resources/assets. Similarly, the participants detected significantly less IEDs when they had eight robots. Participants with higher SpA detected more insurgents, as well as more IEDs. These

results are consistent with previous findings that individuals with higher SpA tend to exhibit more effective scanning performance and, therefore, are able to detect more targets than those with lower SpA (Chen et al., 2008; Chen and Joyner, 2009; Chen and Terrence, 2008, 2009; Chen and Clark, 2008). It is likely that the utility of RoboLeader was not sufficient to overcome the effect of SpA. In other words, the participants with higher SpA were able to outperform those with lower SpA, regardless of the RoboLeader condition. Additionally, there was a non-significant trend toward a difference between higher and lower SpA participants in their IED detection performance when they had access to RoboLeader. Those with lower SpA did not seem to benefit from RoboLeader as much as their higher SpA counterparts. It is likely that the lower SpA participants' scanning of the streaming videos on the OCU was more disrupted by their interaction with RoboLeader; on the other hand, the higher SpA participants' scanning was more effective and less affected by their interaction with RoboLeader. Future research can benefit from investigating the effects of SpA on the scanning behaviors of robotics operators.

When there were eight robots, participants' SA was significantly worse than when there were only four robots. On the other hand, the SA of the RoboLeader participants was not significantly degraded compared with the Baseline group. In other words, the "out-of-the-loop" phenomenon associated with automation (Chen and Joyner, 2009; Parasuraman, Molloy, and Singh, 1993; Young and Stanton, 2007) was not manifested in the RoboLeader condition.

Participants experienced significantly higher workload when there were eight robots compared to the four-robot condition, and those with better attentional control reported lower workload than did those with poorer attentional control. Females also reported significantly higher workload than did males. Those participants in the RoboLeader group rated their workload as slightly lower than did those in the Baseline group, although the difference did not reach statistical significance.

5. Transitions

RoboLeader will be used to support our Year Two (FY10) Director's Research Initiative (DRI) work, in which the capabilities of RoboLeader will be expanded to deal more specifically with research on dynamic re-tasking requirements for persistent surveillance of a simulated urban environment based on various battlefield developments (e.g., individual robots need to be re-tasked to search for a high-stake target). Furthermore, the capability of RoboLeader will be extended beyond the coordination with homogeneous assets (i.e., unmanned ground vehicles [UGVs]) to coordination with heterogeneous assets (i.e., unmanned aerial vehicles [UAVs] and UGVs) when in pursuit of moving targets in urban environments. Additionally, RoboLeader will be used for studies of automation reliability and operator individual differences in future Safe Operations for Unmanned Reconnaissance in Complex Environments (SOURCE) Army Technology Objective (ATO) research.

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Appendix A. Demographic Questionnaire

This appendix appears in its original form without editorial changes.

Participant # _______ Age ______ Major ________________ Date ___________ Gender ___

1. What is the <u>highest</u> level of education you have had?
Less than 4 yrs of college ____ Completed 4 yrs of college ____ Other ____

2. When did you use computers in your education? (*<u>Circle all that apply</u>*)

Grade School	Jr. High	High School
Technical School	College	Did Not Use

3. Where do you currently use a computer? (*<u>Circle all that apply</u>*)

Home   Work   Library   Other________   Do Not Use

4. For each of the following questions, <u>circle</u> the response that best describes you.

How often do you:	
Use a mouse?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use a joystick?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use a touch screen?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use icon-based programs/software?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use programs/software with pull-down menus?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use graphics/drawing features in software packages?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Use E-mail?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Operate a radio controlled vehicle (car, boat, or plane)?	Daily, Weekly, Monthly, Once every few months, Rarely, Never
Play computer/video games?	Daily, Weekly, Monthly, Once every few months, Rarely, Never

5. Which type(s) of computer/video games do you most often play if you play at least once every few months?

6. Which of the following best describes your expertise with computer? (check √ one)
_____ Novice
_____ Good with one type of software package (such as word processing or slides)
_____ Good with several software packages
_____ Can program in one language and use several software packages
_____ Can program in several languages and use several software packages

7. Are you in your usual state of health physically? YES NO
If NO, please briefly explain:

8. How many hours of sleep did you get last night? ______ hours

9. Do you have normal color vision? YES NO

10. Do you have prior military service? YES NO If Yes, how long __________

Appendix B. Attentional Control Survey

This appendix appears in its original form without editorial changes.

For each of the following questions, circle the response that best describes you.

It is very hard for me to concentrate on a difficult task when there are noises around.
Almost never, Sometimes, Often, Always

When I need to concentrate and solve a problem, I have trouble focusing my attention.
Almost never, Sometimes, Often, Always

When I am working hard on something, I still get distracted by events around me.
Almost never, Sometimes, Often, Always

My concentration is good even if there is music in the room around me.
Almost never, Sometimes, Often, Always

When concentrating, I can focus my attention so that I become unaware of what's going on in the room around me. Almost never, Sometimes, Often, Always

When I am reading or studying, I am easily distracted if there are people talking in the same room.
Almost never, Sometimes, Often, Always

When trying to focus my attention on something, I have difficulty blocking out distracting thoughts.
Almost never, Sometimes, Often, Always

I have a hard time concentrating when I'm excited about something.
Almost never, Sometimes, Often, Always

When concentrating, I ignore feelings of hunger or thirst. Almost never, Sometimes, Often, Always

I can quickly switch from one task to another. Almost never, Sometimes, Often, Always

It takes me a while to get really involved in a new task. Almost never, Sometimes, Often, Always

It is difficult for me to coordinate my attention between the listening and writing required when taking notes during lectures. Almost never, Sometimes, Often, Always

I can become interested in a new topic very quickly when I need to.
Almost never, Sometimes, Often, Always

It is easy for me to read or write while I'm also talking on the phone.
Almost never, Sometimes, Often, Always

I have trouble carrying on two conversations at once. Almost never, Sometimes, Often, Always

I have a hard time coming up with new ideas quickly. Almost never, Sometimes, Often, Always

After being interrupted or distracted, I can easily shift my attention back to what I was doing before.
Almost never, Sometimes, Often, Always

When a distracting thought comes to mind, it is easy for me to shift my attention away from it.
Almost never, Sometimes, Often, Always

It is easy for me to alternate between two different tasks. Almost never, Sometimes, Often, Always

It is hard for me to break from one way of thinking about something and look at it from another point of view.
Almost never, Sometimes, Often, Always

Appendix C. NASA-TLX Questionnaire

This appendix appears in its original form without editorial changes.

Please rate your <u>overall</u> impression of demands imposed on you during the exercise.

1. Mental Demand: How much mental and perceptual activity was required (e.g., thinking, looking, searching, etc.)? Was the task easy or demanding, simple or complex, exacting or forgiving?

LOW |---|---|---|---|---|---|---|---|---|---| HIGH
1 2 3 4 5 6 7 8 9 10

2. Physical Demand: How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

LOW |---|---|---|---|---|---|---|---|---|---| HIGH
1 2 3 4 5 6 7 8 9 10

3. Temporal Demand: How much time pressure did you feel due to the rate or pace at which the task or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

LOW |---|---|---|---|---|---|---|---|---|---| HIGH
1 2 3 4 5 6 7 8 9 10

4. Level of Effort: How hard did you have to work (mentally and physically) to accomplish your level of performance?

LOW |---|---|---|---|---|---|---|---|---|---| HIGH
1 2 3 4 5 6 7 8 9 10

5. Level of Frustration: How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

LOW |---|---|---|---|---|---|---|---|---|---| HIGH
1 2 3 4 5 6 7 8 9 10

6. Performance: How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

LOW |---|---|---|---|---|---|---|---|---|---| HIGH
1 2 3 4 5 6 7 8 9 10

Appendix D. SA Queries

This appendix appears in its original form without editorial changes.

- Use the provided map to identify where your robots are currently located
- Use the provided map to identify which robot has searched the highlighted area
- Which robot has encountered the most IEDs?
- Which robot has encountered the most insurgents?
- What was the name of the last route you edited?
- Which route was edited to perform reconnaissance in a High Priority Area?
- Which route has been edited to avoid a Hostile Area?
- Which robot is closest to finishing their route?
- Which route has encountered an IED explosion?

List of Symbols, Abbreviations and Acronyms

ANCOVA	Analysis of Covariance
ARL	U.S. Army Research Laboratory
ATO	Army Technology Objective
DRI	Director’s Research Initiative
IED	improvised explosive device
MIX	Mixed Initiative Experimental
OCU	operator control unit
PAC	perceived attentional control
SA	situation awareness
SpA	spatial ability
TLX	Task Load Index
UV	unmanned vehicle
UAV	unmanned aerial vehicle
UGV	unmanned ground vehicle

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